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Original Article

Mapping of Spatial Variability of Soil Organic Carbon Based on Radial Basis Functions method

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Abstract

Soil organic carbon (SOC) plays an important role in soil physico-chemical processes as well as in soil fertility and soil quality. Management of SOC can reduce soil erosion and improve crop productivity. Accurate estimation of SOC variability could provide critical information for understanding nutrients cycling and sediment. In this study, Radial Basis Functions (RBF) method was used to investigate the spatial pattern of SOC in the Kouhin watershed in Qazvin province, Iran. SOC values for 110 surface soil samples were measured using standard methods. The performance of the interpolation technique, in term of the accuracy of prediction, was assessed by comparing the deviation of estimates from the measured data by performing a cross-validation technique over the validation dataset (20% data) by using the Root Mean Square Error (RMSE). The results showed that RBF method can be used as effective approach for mapping of spatial variability of soil organic carbon.
Keywords: interpolation, spatial variability, soil organic carbon, Radial Basis Functions.

1. Introduction

Soil organic carbon (SOC) is one of the most important indicators of soil fertility, productivity and quality. Decline in SOC creates an array of negative effects on land productivity [1].

Hence maintaining and improving its level is a pre-requisite to ensure soil quality, crop productivity and sustainability of agricultural ecosystems [2]. Interpolation is the procedure of predicting the value of attributes at unsampled sites from measurements made at point locations within the same area.

Interpolation is used to convert data from point observations to continuous fields so that the spatial patterns sampled by these measurements can be compared with spatial patterns of other spatial entities. The rationale behind spatial interpolation is the very common observation that, on average, values at points close together in space are more likely to be similar than points further apart.

Optimizing spatial sampling scheme to reduce sampling density and estimation of unsampling values can save time and costs [3,4].

However, its effectiveness relies on the accuracy of the spatial interpolation used to define the spatial variability.

Multivariate techniques such as geostatistics have been widely used as estimation tools. Geostatistics provides descriptive tools to directly

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implements the prediction of an attribute at an unsampled location according to known data points within a local neighborhood surrounding [5]. Many comparisons of various interpolation techniques have been made in respect to different data sets used, different mathematical procedures and different input parameters [6,7].

The structure of variability in soil properties showed differences according to sampling spacing, soil properties, and method used in the study [8]. McBratney et al. (2003) provided the comprehensive maps for physical, chemical and biological soil properties by means of geostatistics, GIS and remote sensing techniques for a large area in Australia [9]. Meul et al. (2003) used ordinary kriging, comprehensive kriging, simple kriging and cokriging methods for estimation of silt content in Belgium [10]. They also considered digital elevation model (DEM) as a secondary variable and the results showed that the comprehensive kriging method had the lowest estimating error. Ersahin (2003) used kriging and cokriging methods and soil bulk density as an auxiliary variable for investigation of the spatial variations of infiltration rate in northwest of Turkey [11]. The findings revealed that the cokriging method is a suitable technique for estimation of infiltration rate.

Many other studies also compared Kriging, IDW (Inverse Distance Weighting) and RBF (Radial Basis Functions) in soil science. Gotway et al. (1996) found that the IDW method generated more accurate results than Kriging for mapping soil organic matter and soil NO_3 levels [12]. Robinson and Metternicht (2006) used three different techniques including cokriging, IDW and spline for prediction of the levels of the soil salinity, acidity and organic matter [7]. They recognized the spline and cokriging methods are the best approach for estimation of the soil salinity values and organic matter content. Schloeder (2001) observed that Ordinary Kriging (OK) and IDW were similarly accurate and effective methods, while thin-plate smoothing spline with tensions was not [13]. Weller et al. (2002) concluded that even in cases where the assumptions for Kriging were not fulfilled the Kriging approach was as good as any other radial base function interpolation [14]. Summarising the above, the accuracy of each method depends on the assumptions and subjective judgments that are made, such as the application of smoothness of the results or not and linearity of interpolation functions or not [13].

Apart from research studies to judge the quality of a technique's performance, validation or accuracy assessment of a method is rarely done in operational applications because of its high cost [15]. This study aimed to characterize SOC in semi-arid ecosystem of Kouhin region in Qazvin province, Iran, and particularly to: (1) investigate the spatial pattern of SOC using RBF method and (2) establish a baseline data on SOC stocks for future studies of SOC dynamics.

2. Material and Method

2.1. Site description

The study was carried out in Kouhin region, Qazvin province in Iran (fig. 1). Height amplitude varies from 1300 m to 1600 m above sea level having 1 to 6 percent slope. This belt covers about 1000 hectares, situated between latitude of 36° 20' to 36° 23' north and longitude of 49° 34' to 49° 38' east. The selected area climate is semi-arid in nature. The soil temperature and moisture regimes are mesic and xeric, respectively [16]. Solis have been developed on the surface of alluvial deposits of marl and brown to grey limestone parent materials and is covered by plateau from east to west direction. According to US soil taxonomy system, the soils have been classified as Entisols and Inceptisols [17] and are used for rainfed farming. During 1993-2006, the average annual rainfall and average annual temperature were recorded to be 327 mm and 11.2 ^{0}C, respectively (Iran Meteorological Organization).

2.2. Data collection and soil sample analysis

Grid method was used for sampling and the dimensions were 300 m by 300 m. Few samples were taken from off-grid to present different physiographic positions and total 110 samples of soil (0 to 20 cm depth) were taken. Geographical location of sampling points was recorded by Global Positioning System (GPS). The collected soil samples were air dried, crushed and sieved using 2 mm sieve size and subjected to analysis. Soil properties such as particle size distribution [18], organic carbon (OC) content [19] and CEC [20] were measured.

2.3. Radial Basis Functions in spatial interpolation

Deterministic interpolation techniques create surfaces from measured points, based on either the extent of similarity (Inverse Distance Weighted) or the degree of smoothing (Radial Basis Functions). Radial Base Function methods are considered as exact interpolation techniques. The exact interpolators predict values identical with those measured at the same point and the generated surface requires passing through each measured points. The predicted values can vary above the maximum or below the minimum of the measured values [21]. There are five different basis functions: thin- plate spline, spline with tension, completely regularised spline, multi-quadratic function and inverse multi-quadratic function.

There is a small difference between basis functions and the generated surfaces are slightly different [22].

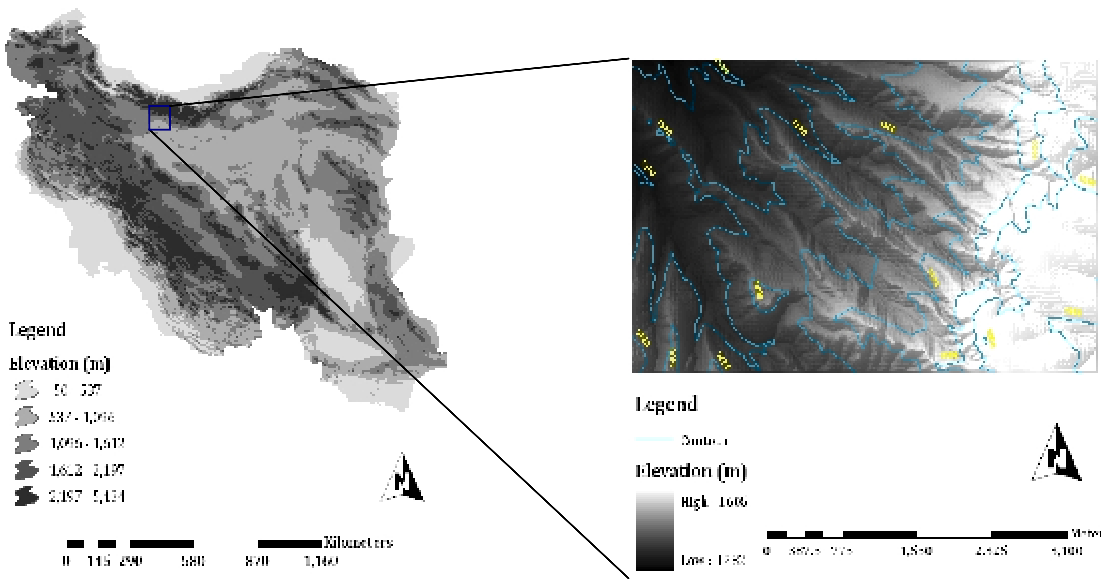

Figure 1. Location of study area

The estimated values of the methods are based on a mathematical function that minimises total curvature of the surface, generating quite smooth surfaces. The smoothness of the resulting surface is controlled by a smoothing parameter. A formula *f*, which minimizes the following factor (eq. 1) is an example of RBF technique and more specifically of the exact spline method:

$$A(f) + \sum_{i=1}^{n} w_i^2 [f(x_i) - y(x_i)]^2 \qquad (1)$$

Where $y(xi)=z(xi)+\varepsilon(xi)$ is the source of random error, where *z* is the measured value of an attribute at point *xi* and epsilon is the associated random error. The term *A*(*f*) represents the smoothness of the function *f* and the second term represents its proximity to the data [15].

2.4. Evaluation procedure

In this study, the performance of the interpolation technique, in term of the accuracy of prediction, was assessed by comparing the deviation of estimates from the measured data by performing a cross-validation technique over the validation dataset (20% data) by using the Root Mean Square Error (RMSE) (eq. 2).

$$RMSE = \sqrt{\sum_{i=1}^{N} (y_o - y_p)^2 / N} \qquad (2)$$

Where y_o, y_p and N are representing the measured, predicted and total number of data points, respectively. The RMSE was used to measure accuracy and validity of the validation data set.

In a cross-validation procedure each data point is removed from the data set, one at a time, and predicted value is return by performing interpolation algorithm on the rest of dataset.

This yield a list of estimated values of variable data paired to the test data. Finally, the spatial distribution map of SOC was plotted using ArcGIS (10.1) software.

3. Results and discussion

3.1. Exploratory data analysis

Exploratory analysis including descriptive statistics (table 1) and global trend of SOC was implemented using the 'Geostatistical Analyst' of ArcGIS 10.1 software package. Global trend is an overriding process that affects all measurements in a deterministic way. This is achieved by projecting the sample locations on an *x*, *y* plane. The value of the attribute of each sample is given in the *z* dimension. Moreover, the values of the attributes are projected on *x*, *z* and *y*, *z* planes as scatter plots. Global trend exists if a curve that is not flat (i.e., a polynomial line) can fit through the data. For the soil samples of the study area, trend analysis showed that SOC had a trend in the direction SW to NE (fig. 2).

Table 1. Data summary statistics of soil parameters

Variable	Unit	Mean	Min	Max	Skewness	Kurtosis	C.V (%)
Clay	(%)	40.70	25	59	-0.18	0.82	22.59
Silt		26.30	16	44	0.60	0.66	21.70
Sand		32	10	57	0.43	0.33	34.95
OC		0.68	0.13	1.33	0.39	0.69	42.64
CEC	$Cmol^{+}kg^{-1}$	23.08	17.03	29.43	0.13	0.38	12.35

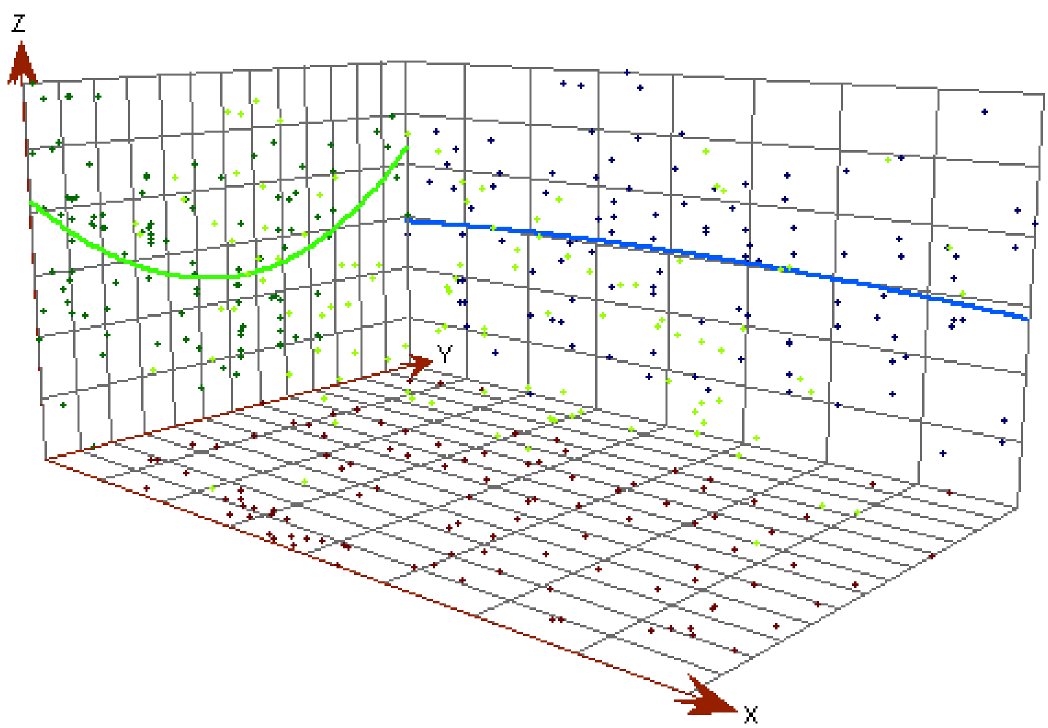

Figure 2. Trend analysis of soil organic carbon

As it is also highlighted in table 1, relatively wide range of variations was observed in soil properties. Variation of 25 to 59% was recorded in clay particles, whereas OC content varied from 0.13 to 1.33% with an average value of 0.68.

The coefficient of variation (C.V) of SOC was found to be high, which might be due the application of fertilizers and resultantly, improvement in the soil OC property is expected. Similar to this study, [23] also reported a high coefficient variation of soil organic matter and correlated it with fertilizer application.

3.2. Interpolation

The parameters used in interpolation procedure for creating the prediction map of soil organic carbon are presented in table 2.

Table 2. Parameters of the interpolation method (RBF) for SOC

Interpolation method	Kernel Function	Parameter	Anisotropy factor	RMSE (%)
Radial Basis Functions	Spline with tension	0.52635	1	0.260

3.3. Prediction map of soil organic carbon

The final prediction map of SOC developed using RBF method can be seen in fig. 3. The SOC value decreased from the southern to northern part in the study area and elevation and slope gradient increased in this direction. These results suggest that particularly in the topsoil the spatial distribution patterns of SOC can be highly variable due to small scale variations in input, redistribution, stabilization, as well as in intrinsic random variability of SOC.

This might relate to strong influence of climate and ecosystem properties including soil properties, such as clay content and mineralogy [24]. Additionally, the sampling scheme may also affect the prediction of desired parameter. Land use may affect the relationship among variables and previous studies also demonstrated similar results [25-27]. Land use information helped to improve model precision.

Previous researches indicate that land use change has major impact on soil organic carbon storage [28-30]. Results presented here could be interpreted that the impacts of current land use on the distribution of SOC are relatively small compared with topographic impacts. Furthermore, land use itself is determined by the topographic conditions and some of the land use impacts had already been represented in the topographic derived parameters [31].

The use of auxiliary data such as geology and land use or soil type as well as sub-division of study area may improve the prediction by reducing the overall variability and better to highlight the SOC relationship with environmental predictors.

A major limitation of grid sampling is that a large number of samples are required to resolve the spatial variability in soil nutrient levels, which could be highly complex within field [32].

In addition, the topography influences soil properties due to local re-distribution of water, solar radiation and soil material [32, 33]. Several factors could be involved for the deduction of optimal response such as different types and morphology of clay and spatial variability of soil properties etc.

So, for the optimization of response with more accuracy, homogeneity in soil is required.

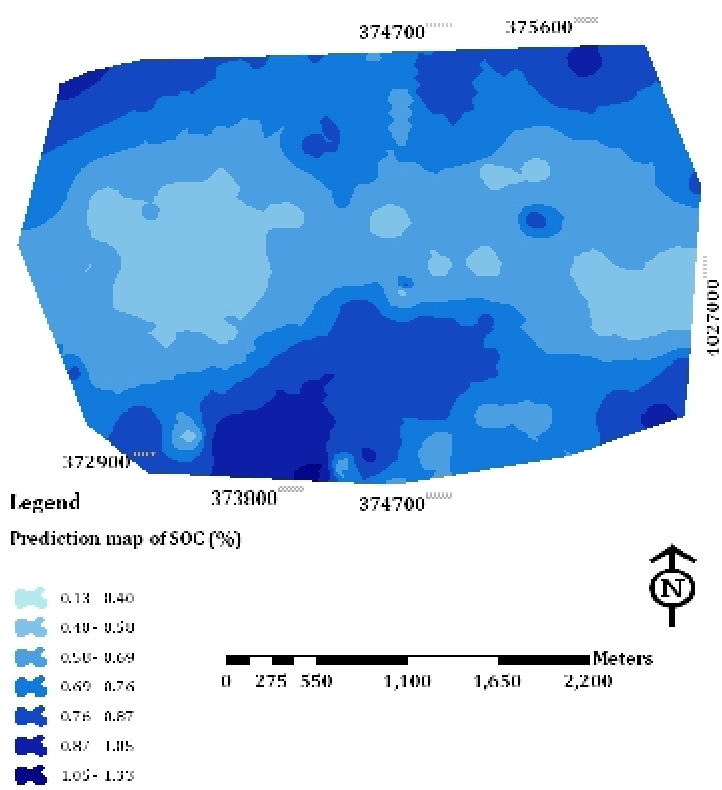

Figure 3. Prediction map of soil organic carbon using RBF method

4. Conclusions

In this study, Radial Basis Functions (RBF) method was used to investigate the spatial pattern of SOC in the Kouhin region, Qazvin province, Iran. Accuracy assessment carried out using root mean square error (RMSE). The results indicated that RBF interpolation method needed to adjust the parameter and the search radius to improve accuracy. Overall, the processes of analyzing the global trends and choice of search neighborhoods required much time and effort. However, RBF interpolation method showed satisfactory results for SOC prediction map. It is desirable to compare these results with other interpolation methods at different scale.

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